MANAGEMENT OF A SHARED, AUTONOMOUS, ELECTRIC VEHICLE FLEET: IMPLICATIONS OF PRICING SCHEMES

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ABSTRACT
This paper models the market potential of a fleet of shared, autonomous, electric vehicles (SAEVs) by employing a multinomial logit mode choice model in an agent-based framework and different fare settings. The mode share of SAEVs in the simulated mid-sized city (modeled roughly after Austin, Texas) is predicted to lie between 14 and 39%, when competing against privately-owned, manually-driven vehicles and city bus service. This assumes SAEVs are priced between $0.75 and $1.00 per mile, which delivers significant net revenues to the fleet owner-operator, under all modeled scenarios, assuming 80-mile-range electric vehicles and remote/cordless Level II charging infrastructure and up to $25,000 of per-vehicle automation costs. Various dynamic pricing schemes for SAEV fares show that specific fleet metrics can be improved with targeted strategies. For example, pricing strategies that attempt to balance available SAEV supply with anticipated trip demand can decrease average wait times by 19 to 23%. However, tradeoffs also exist within this price-setting: fare structures that favor higher revenue-to-cost ratios (by targeting high-value-of-travel-time [VOTT] travelers) reduce SAEV mode shares, while those that favor larger mode shares (by appealing to a wider VOTT range) produce lower payback.

KEYWORDS
Carsharing, autonomous vehicles, electric vehicles, mode choice, travel costs, taxis

INTRODUCTION
Technology is quickly changing the landscape of urban transportation. With mobile computing enabling the fast rise of the shared-use economy, carsharing is emerging as an alternative mode that is more flexible than transit but less expensive than traditional (private-vehicle) ownership. Electric vehicle (EV) sales are on the rise with plug-in EVs' market share growing from 0.14% in 2011 to 0.67% in 2014 (Plug in America 2015).Growing plug-in EV adoption should be helpful to most regions in achieving air quality standards for ozone and particulate matter, and ultimately greenhouse gases. Motivated by roadway safety and the growing burden of congested urban driving, automated driving technologies are emerging and private purchases of self-driving vehicles may be possible by 2020 (Bierstadt et al. 2014).

There are natural synergies between shared AV (SAV) fleets and EV technology. SAVs resolve the practical limitations of today's non-autonomous EVs, including traveler range anxiety, access to charging infrastructure/special outlets, and charge-time management. A fleet of shared autonomous electric vehicles (SAEVs) relieves such concerns, by managing range and charging activities based on real-time trip demand and established charging-station locations, as demonstrated in Chen et al. (2016). However, when SAEVs make their debut in cities, these vehicles will not exist in a vacuum. SAEVs will be competing against existing modes (private owned vehicles, transit, and non-motorized modes) for trip share. In this paper, a mode choice model is added to Chen et al.'s (2016) agent-based framework in order to anticipate SAEV market shares in direct competition with other modes. A fleet of 80-mile-range SAEVs is paired with Level II charging infrastructure to deliver relatively fleet operations, and a variety of pricing strategies are employed while examining the shifting mode shares.

PRIOR RESEARCH

Recent research has examined the operations of self-driving vehicles in a shared setting, primarily focusing on metrics like empty-vehicle miles traveled (VMT), average wait times, and private vehicle replacement rates (Kornhauser et al. [2013], Fagnant and Kockelman [2014], Spieser et al. [2014], ITF [2015], Chen et al. [2016], etc.). Very few have yet simulated AV effects in competition with other modes of travel.

Levin and Boyles (2015) recently simulated mode choice of privately-owned AVs (versus transit, private car travel, and walk/bike) with a fixed trip table for a small (downtown) section of Austin, Texas. Their model allows such AVs to strategically re-position themselves to avoid high parking fees (while incurring added fuel costs, but no traveler time costs), and uses dynamic traffic assignment over a 2-hour peak (morning) period. Their special test cases showed transit demand falling as more user classes (segmented by value of travel time [VOTT]) had access to AVs, with 61% of low-VOTT travelers decreasing their transit use. They allowed link capacities to rise as a function of the proportion of AVs on each link, so congestion did not worsen as the number of vehicle trips rose sharply (due to empty-vehicle parking repositioning). Childress et al. (2015) used Seattle, Washington's activity-based travel model (including short-term travel choices and long term work-location and auto-ownership choices) to anticipate AV technology impacts (from higher roadway capacities, lowered VOTTs, reduced parking costs, and increased car-sharing) on regional travel patterns. Their model estimated that higher income households are more likely to choose the AV mode, as expected (since the technology is costly and alternate use of in-vehicle time VOTT reductions for higher-VOTT travelers are likely to be more significant). With SAVs priced at $1.65 per mile (reflecting costs of current ride-sharing taxi services, like Lyft and Uber), drive-alone trips were predicted to fall by one-third and transit shares rose by 140%, as households released traditional vehicles and acquired AVs or turned to SAVs along with other travel options, since they were no longer "tied" to the fixed cost (and round-trip restrictions) of vehicle ownership and storage.

The above two simulations are largely limited to private AV ownership (except for one scenario [out of four] in Childress et al. [2015]). Furthermore, their mode choice simulations assumed fixed prices/costs for AV (and SAV) use. Due to the variable nature of SAV availability and user wait times, as well as different costs associated with empty VMT for refueling SAVs and passenger pick-up, SAV pricing may best be "smart-priced" to improve fleet performance metrics. The agent-based framework employed in this paper allows for mode choice in the context of each trip (based on a trip's time-of-day [to allow for "surge pricing" during peak demand periods] and distance, and its traveler's VOTT) and follows SAEV fleet utilizationthrough a series of simulated travel days to appreciate the effects of various dynamic pricing strategies on mode shares and SAV trip-making behaviors.

METHODOLOGY

The model in this paper builds off of Chen et al.'s (2016) discrete-time agent-based model, which examines the operations of SAEVs and conventionally-fueled SAVs serving roughly 10% of all trips in a 100-mile by 100-mile region. The simulation is gridded to quarter-mile by quarter-mile trip generation and service cells, as shown in Figure 1. Similar to Chen et al. (2016), the trip generation process used here produces each trip based on an average daily rate for each cell (which depends on the local population density, and thus the Euclidean distance to the regional centerpoint in this idealized region), then assigns the destination cell based on trip distance (drawn from the U.S. 2009 National Household Travel Survey's [NHTS's] distribution). Average daily trip rates (as shown in Table 1) represent 100% of trips in the simulated region, with rates roughly following the population densities and trip generation rates of Austin, Texas' travel demand model. Here, a multinomial logit (MNL) mode choice model is added to the agent-based model to allow all trips in the region to choose among private vehicle, transit, and SAEV modes. Trips less than 1 mile in distance (under the NHTS 2009 distribution) are not studied here, since such travelers may often prefer to walk. Since most walking trips in the U.S. are under 1 mile in length, and bike trips are few in the U.S.(Santos et al. 2011), non-motorized modes are not simulated here.

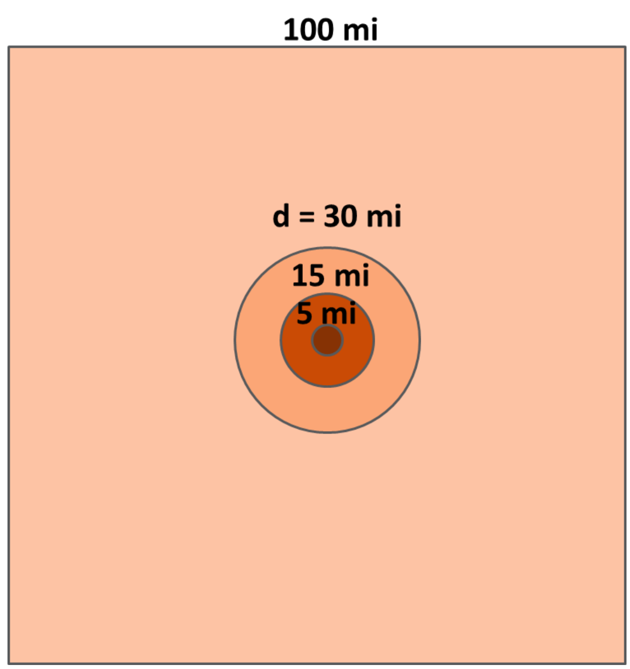

Figure 1. Regional Zones System

Table 1. Total (Motorized) Trip Generation Rates and Travel Speeds by Zone

	Population Density (persons/mi^2)	Avg Trip Gen. Rate (trips/cell/day)	SAEV Travel Speed (mi/hr)	
			Peak	Off-Peak
Downtown	7500-50,000	1287	15	15
Urban	2000-7499	386	24	24
Suburban	500-1999	105	30	33
Exurban	<499	7	33	36

The amount of money travelers are willing to pay to save travel time and distance varies with each traveler, trip type, day of week, and even driver's state of mind. To relate each trip to an individual traveler and his/her mode choice in this model, a VOTT is generated for each trip, based on trip purposes and wage rates (per hour). According to the 2009 NHTS, 18.7% of person-trips per household are for work and work-related business trips (Santos et al. 2011). The other 81.3% of trips (for shopping, family/personal errands, school, worship, social, and recreational activities) are combined here, as non-work. After randomly assigning a trip purpose, an income is assigned for the individual traveler based on US Census (2009) data on personal income of individuals residing inside metropolitan areas. SAVs presumably operate more efficiently in densely developed locations than sparsely populated areas (Burns et al. 2013, Fagnant and Kockelman 2015), and individual incomes in metro areas tend to be higher than those in rural areas (with personal incomes averaging 33 percent higher, according to US Census [2009]). Hourly wages used in the model here are derived from 2009 Census data on personal income of this living inside metropolitan areas (an average of $48,738 per person per year), and converted to an hourly wage assuming 2000 work hours per year.(US Census 2009).Using USDOT (2011) guidelines, VOTT is assumed to be 50% of hourly wage for personal trips and 100% of hourly wage for business/work trips, yielding Figure 2's VOTT distributions.

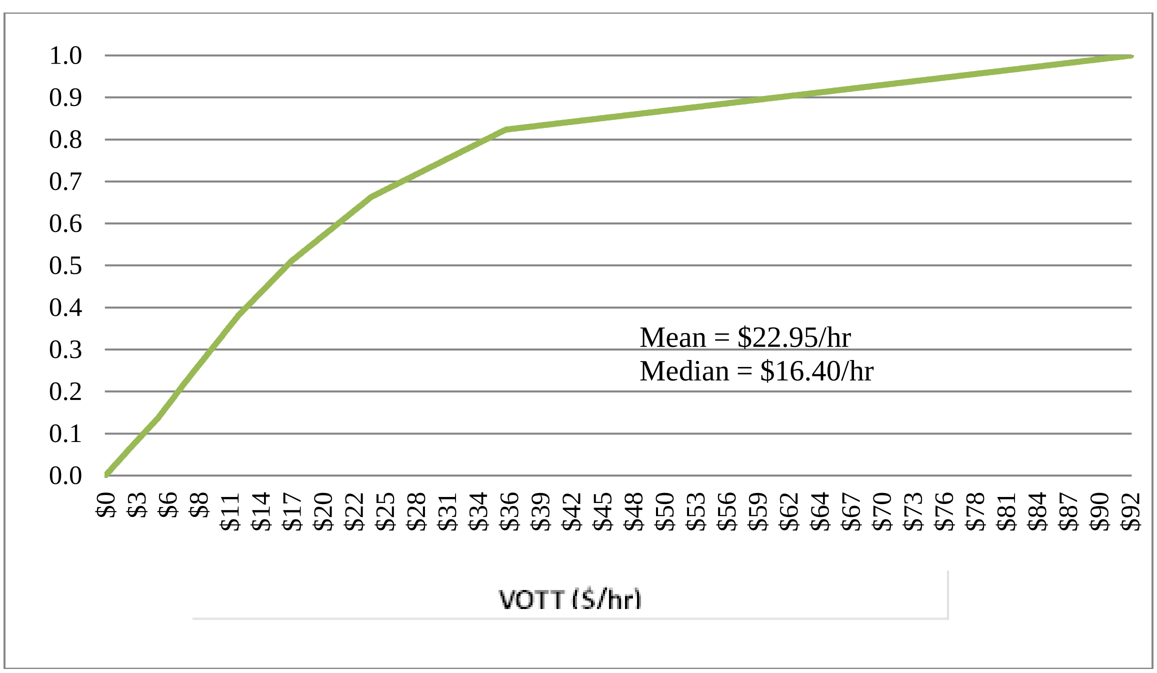

Figure 2a. Work Trips

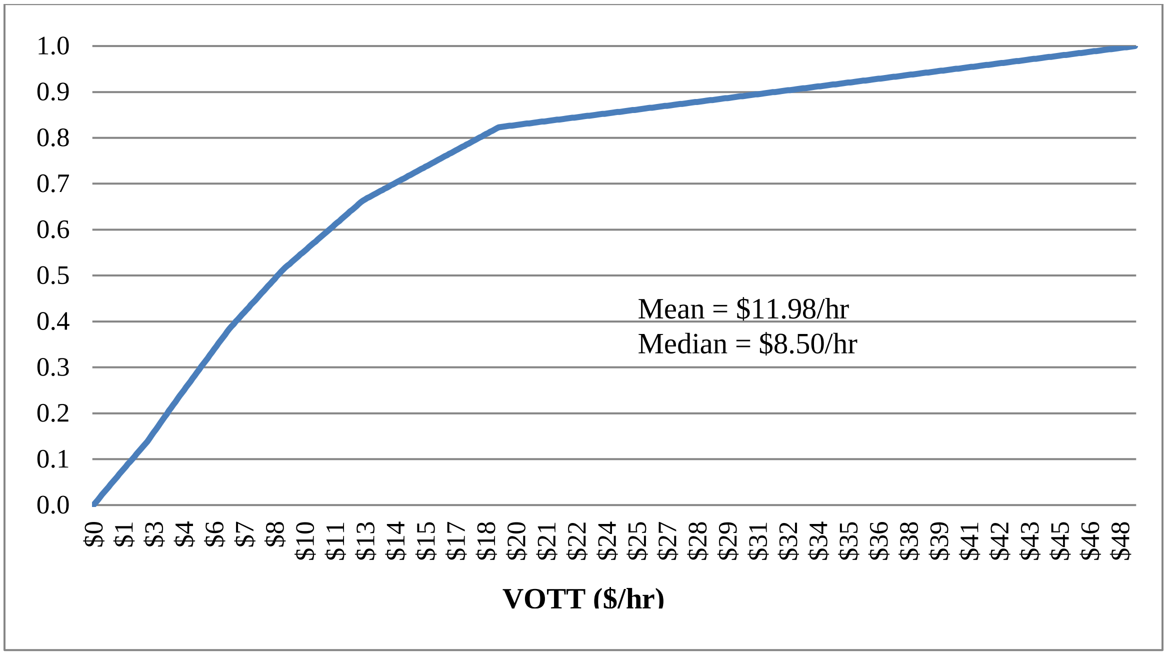

Figure 2b. Non-Work Trips

Figure 2. VOTT Distributions for Work (2a) and Non-Work (2b) Trips

In an MNL model, the probability of an individual choosing an alternative is assumed to monotonically increase with that alternative's systematic utility (Koppelman and Bhat 2006), assuming all other modes' attributes remain constant, and can be expressed as the following:

$$\Pr(i) = \frac{\exp(V_i)}{\exp(V_{PV}) + \exp(V_{Transit}) + \exp(V_{SAEV})} \quad (1)$$

where i denotes the alternative for which the probability is being computed; V_{PV}, $V_{Transit}$, and V_{SAEV} denote the systematic utilities of private vehicle, transit, and SAEV, respectively, for a specific origin-destination-traveler-time of day trip.

Private Vehicle

In this mode choice model, private vehicle utility is modeled as a function of VOTT, operating costs, and parking fees in the destination zone as seen in the equation below:

$$V_{PV} = -VOTT\left(\frac{Distance_{trip}}{Speed_{PV}}\right) - \$0.152\,(Distance_{trip}) - Parking_D \quad (2)$$

where $VOTT$ is the individual monetary valuation of value of travel time drawn from distributions in Figure 2, $Distance_{trip}$ is the distance of the requested trip, $Speed$ is equivalent to SAEV average speeds shown in Table 1), $0.152 is the equivalent vehicle operating cost per cell based on AAA's (2014) estimate of \$0.608 per mile, and $Parking_D$ is the parking fee in the destination zone. In this model, parking cost is assumed to be \$0 for all business trips, since 95% of commuters who drive to work park for free at the workplace (Shoup and Breinholt 1997) and other business transportation are often priced in a distorted market with expense accounts. For personal trips, parking for private vehicles is assumed to be \$0 for trips that end in suburban or exurban cells, \$2 for trips that end in urban cells, and \$4 for trips that end in downtown cells.

Transit

For simplification, the transit mode modeled here emulates local city bus service, the most common form of transit in US cities. Similar to private vehicles, the utility of the transit mode also depends on transit travel speeds and individual traveler's VOTT. In addition, access time and fare are considered in the transit utility equation below:

$$V_{transit} = -(2)\left(\frac{VOTT}{60}\right)(AT_O + AT_D) - VOTT\left(\frac{Distance_{trip}}{Speed_{transit}}\right) - Fare_{\ transit} \tag{3}$$

Where $Speed_{transit}$ is modeled at 25% slower than Table 1's SAEV speeds during off-peak hours and 20% slower during peak hours due to stops (roughly based on Austin's travel demand model's travel time skims), \$2 is the assumed one way $Fare_{transit}$ based on the \$2.04 per unlinked trip fare average from the 2013 National Transit Database Urbanized Data (APTA 2013), and AT_O and AT_D are the access and wait times in minutes based on the trip's origin and destination cell following Table 2.

Table 2. Transit Access & Wait Time by Zone

Zone	Transit Access & Wait Time (min.)
Downtown	3
Urban	9
Suburban	21
Exurban	60

Transit access and wait time for exurban cells are penalized (valued at 60 minutes) in the utility function due to the fact that most transit trips to and from exurban areas require transfers (either from private car to transit, or one bus route to another bus route) in the majority of local bus service route designs. Furthermore, access time for transit is modeled at double the VOTT compared to in-vehicle travel time (IVTT). This penalty reflects the general discomfort of time spent walking, bicycling, and waiting outside of vehicles as compared to being inside a vehicle, as recommended in Wardman (2014). Though seated IVTT on transit modes is typically valuated as less onerous than IVTT in a private car (presuming that the traveler can perform more productive or leisure activities while seated on a bus as compared to driving a car), standing IVTT on transit modes is considered more onerous than driving a private vehicle (Wardman 2014). Thus, in this model, transit IVTT is simplified to be valued the same as private vehicle IVTT.

SAEV

The structure of the SAEV utility valuation (Equation 4) is similar to that of transit, except where transit utility is modeled with a simplified flat price, the SAEV mode incorporates several pricing schemes to examine the impact of pricing on SAEV mode share and fleet operations. The SAEV utility is expressed as:

$$V_{SAEV} = -(2)\left(\frac{VOTT}{60}\right)(2.5 + 5n_{wlist}) - (0.35)VOTT\left(\frac{Distance_{trip}}{Speed_{SAEV}}\right) - Fare_{SAEV} \quad (4)$$

Where n_{wlist} is the number of time steps a trip has been on the SAEV waitlist and $Fare$ is the traveler out-of-pocket cost. The first term of this utility function models the onerousness of waiting for an SAEV, valuated at double the IVTT as is done in the transit utility equation. When a trip is generated, the traveler assumes the wait time is 2.5 minutes (half of a time step). If the trip is waitlisted, the traveler re-evaluates mode choice in each of the subsequent time steps the trip remains on the waitlist, and adds 5 minutes to the wait time for each time step the traveler has been on the waitlist. In other words, the longer a trip remains on the waitlist, the more the SAEV utility decreases, and the less likely the traveler will choose SAEV mode.

The second term of this utility function models the cost of SAEV IVTT. Unlike transit, a traveler will not have to stand in a SAEV. Thus, a traveler can use the IVTT in a SAEV to work, read, listen to music, or pursue other productive or leisure activities. In the base case, this reduction in travel time cost is modeled at 35% of the IVTT in a non-autonomous private vehicle (where the traveler would be driving), equivalent to the valuation of seated riding time on transit (Concas and Kolpakov 2009). This value is varied in the sensitivity analysis section to examine the impact of IVTT valuation on SAEV mode share. SAEV speeds (shown in Table 1) are assumed to be the same as private vehicle speeds.

The last term of the SAEV utility function is the fare. In this model, four pricing strategies are explored: simple distance-based, origin-based, destination-based, and combination pricing. Each pricing scheme is discussed in detail below.

Distance-Based Pricing

In simple distance-based pricing, the fare is determined proportional to the trip distance as seen in Eq. 5. This pricing scheme is similar to the usage-based (by mileage or time) pricing schemes of current non-autonomous carsharing services.

$$Fare_{SAEV} = \$0.2125 \times Distance_{trip} \quad (5)$$

Using overhead costs for similarly scaled transit services and assuming operating margins of 10%, Chen et al. (2016) estimate a fleet of SAEVs can be offered at \$0.66 to \$0.83 per occupied mile of travel, depending on type of fleet vehicles and charging infrastructure. To be conservative, \$0.85 per mile (\$0.2125 per cell) is used as the base fare for simple distance pricing. This per-mile fare is also varied in the sensitivity analysis to examine the effects of higher and lower fares on SAEV market share.

Origin-Based Pricing

Vehicle relocation is one of the biggest challenges facing operators of non-autonomous carsharing services (see, e.g. Barth and Todd 1999, Correia and Antunes 2012). The origin-based pricing in Equation 6 builds off of Correia and Antunes' (2012) suggestion that variable pricing policies which encourage trips to balance the demand and availability of vehicles at carsharing stations could contribute to more profitable operations. Here, origin-based pricing attempts to minimize empty vehicles miles traveled for relocation by incentivizing trips originating in a cell that has a surplus of vehicles and penalizing trips originating in a cell that has a deficit of vehicles.

$$Fare_{SAEV} = (\$0.2125 \times Distance_{trip})SDMultiplier \tag{6}$$

$$\text{where } SDMultiplier = 0.5, \text{ when } \left(\frac{SAEVSupply_{B,t}}{SAEVSupply_{b,t}}\right)\left(\frac{TripDemand_{b,t+1}}{TripDemand_{B,t+1}}\right) < 0.1$$

$$SDMultiplier = 1, \text{ when } 10 > \left(\frac{SAEVSupply_{B,t}}{SAEVSupply_{b,t}}\right)\left(\frac{TripDemand_{b,t+1}}{TripDemand_{B,t+1}}\right) > 0.1$$

$$SDMultiplier = 2, \text{ when } \left(\frac{SAEVSupply_{B,t}}{SAEVSupply_{b,t}}\right)\left(\frac{TripDemand_{b,t+1}}{TripDemand_{B,t+1}}\right) > 10$$

In Eq. 6, $SAEVSupply_{B,t}$ is the total number of available SAEVs across all blocks B in the current time step, $SAEVSupply_{b,t}$ is the number of vehicles available in the 2-mile by 2-mile block b around the origin cell in the current time step, $TripDemand_{b,t+1}$ is the number of trips (based on average generation rates shown in Table 1) anticipated to originate from the 2-mile by 2-mile block b surrounding the origin cell in the subsequent time step, and $TripDemand_{B,t+1}$ is the total trip demand anticipated for the subsequent time step. Essentially, origin-based pricing compares the proportions of trip demand and available vehicle supply in a 2-mile by 2-mile block out of the entire region. Thus, trips that originate in a block with an excess of vehicles (defined by when the product of vehicle supply and trip demand ratios is less than 1) will be cheaper than trips that originate in a block with a deficit of vehicles (defined by when the product of vehicle supply and trip demand ratios is greater than 1). This ratio of ratios is then normalized by the $SDMultiplier$ term, which halves the SAEV fare when supply is at least 10 times greater than demand and doubles the SAEV fare when demand is at least 10 times greater than supply. By incorporating the $SDMultiplier$ term in place of using absolute ratios, extreme pricing scenarios are avoided. It is worth noting that this pricing strategy is rule-based and serves the purpose of illustrating the effect of demand-based pricing on SAEV mode share, but the pricing is not optimized for SAEV fleet performance or profit.

Destination-Based Pricing

As demonstrated in Chen et al. (2016), up to 5% of a SAEV fleet's VMT can be attributed to unoccupied miles traveled for charging purposes. The destination-based pricing scheme in Equation 7 attempts to minimize these empty vehicle miles by incentivizing trips that end in a cell close to a charging station site and penalize trips that end in a cell far away from a charging station site.

$$Fare_{SAEV} = \$0.2125(Distance_{trip} + Distance_{charge}) \tag{7}$$

In Equation 7, $Distance_{charge}$ represents the distance from the destination cell to the closest charging station site. Thus, the destination-based fare prices both occupied miles traveled during the trip and the unoccupied miles traveled to a charging station after a trip is complete.

Combination Pricing

The last fare structure tested here (Equation 8) is simply a combination of origin- and destination-based pricing presented in Equations 6 and 7.

$$Fare_{SAEV} = \$0.2125(Distance_{trip} + Distance_{charge})SDMultiplier \quad (8)$$

RESULTS

In order to understand the impact of introducing a new SAEV mode on existing private vehicle and transit modes, it crucial to examine mode choice in the context of only having the latter two modes. In other words, before introducing SAEVs, what mode would the travelers have chosen for their trips? And what mode will they choose once SAEVs are available?

Two-Mode Model

Mode choice results from the two-mode model are shown in Table 3. Using the private vehicle and transit utility functions described previously, the model yielded 85.2% private vehicle trips and 14.8% transit trips. For comparison, according to the 2009 American Community Survey, 76.4% of US workers who live and work inside the same metropolitan area commute by drive alone mode and 7.8% commute by public transit (McKenzie and Rapino 2011). While trips with low VOTT are served by both private vehicle and transit modes (both with minimum VOTTs of \$0), trips valuated at over \$21.20 per hour are only served by private vehicles. The long right tail of the VOTT distribution for private vehicle trips (with maximum VOTT at \$90.80 per hour) is evident when looking at averages: mean VOTT for a private vehicle trip is 4.5 times the mean VOTT for a transit trip. In a similar manner, short trips are served by both private vehicles and transit, but transit is consistently the preferred mode for longer trips (over 119 miles).

In the simplified transit pricing modeled here, longer trips will incur higher operating costs for private vehicles while fare remains flat at \$2 for transit, hence the preference for transit mode as trip lengths grow longer. Model results also show that where there are significant parking costs, transit is preferred over private vehicle mode. Hypothetically, trips served by transit would have averaged \$1.15 in parking fees per trip had the trips been served by private vehicle. Trips that actually chose private vehicle mode averaged just \$0.32 in parking fees per trip. Likewise, when transit access times are significant, private vehicle mode is preferred. Trips that chose transit mode had an average total origin and destination access time of 44 minutes, while trips that chose private vehicle mode would have hypothetically averaged 74 minutes for origin and destination access had transit mode been chosen.

Table 3. Attributes of Private-Vehicle and Transit Trips in Two-Mode Model

		Private-Vehicle Trips	Transit Trips
Mode Share		85.19%	14.81%
VOTT ($/hr)	Mean	$16.16	$3.56
	Median	$11.40	$2.75
	Std Dev	$15.04	$3.29
	Max	$90.80	$21.20
	Min	$0.00	$0.00
Trip Distance (mi)	Mean	8.83	17.21
	Median	5.00	10.13
	Std Dev	10.83	19.47

	Max	118.50	146.50
	Min	1.00	1.00
Avg Private Vehicle Parking Cost		$0.32	$1.15
Avg Transit Access & Wait Time (min.)		73.70	44.47

Note: Transit trips do not carry parking costs, and PV trips do not involve transit access and wait times. Table values reflect the attributes of the competing (and the chosen) modes.

Three-Mode Model

Simple Distance-Based Pricing

Once SAEVs are introduced into the dynamic mode choice model, there is a significant shift away from private vehicle use. In the results shown in Table 4, SAEVs fares are structured with simple distance-based pricing at $0.85 per trip mile. The model predicts this pricing scheme will attract 27.1% of all trips generated to the SAEV mode while reducing private vehicle and transit mode shares to 60.8% and 12.1%, respectively. Comparing these mode shares to the two-mode results in Table 3, it is clear that SAEVs are drawing the majority (89.9%) of its market share from trips formerly made in private vehicles. The remaining10.1% of SAEV trips come from former transit trips.

Mean VOTT for SAEV trips are higher than that for the other two modes, averaging $19.62 per hour compared to $17.97 for private vehicle trips and $3.62 for transit trips. The average trip distance of SAEV trips (10.7 miles) is in between that of private vehicle trips (7.8 miles) and transit trips (19.4 miles). This model result suggests that SAEVs are attracting higher-income (as reflected by higher VOTT) travelers who take advantage of the leisure or productive time during longer trips in a SAEV that would have otherwise been spent driving a private vehicle, echoing results from Childress et al. (2015). For shorter trips, this in-vehicle leisure time advantage is overshadowed by the cost of the SAEV wait time. Note that due to the 80-mile range limitation of SAEVs modeled here, the maximum distance of a SAEV trip is 77 miles, much shorter than the maximum trip distances of private vehicle and transit modes.

Model results also suggest that SAEVs are replacing some former short transit trips: the average transit trip length increases from 17.2 miles (Table 3) to 19.4 miles (Table 4) once SAEVs are introduced. This is likely due to the fact that for shorter trips traveling between zones served sparingly by transit (such as suburban and exurban zones), the long transit access and wait times inflict disproportionately high travel costs (as compared to the cost of IVTT and fare), thus significantly reducing the utility of the mode. In such cases, a SAEV offers relatively short wait times and, for trips less than 3 miles, a competitive fare to the $2 flat transit price. A look at the average transit wait times for each mode's trips confirms this explanation. SAEV trips would have averaged 68 minutes of access and wait time per trip had they hypothetically selected transit, whereas transit trips average 45 minutes of total access and wait times. Results also confirm that trips which incur no or low parking fees prefer private vehicle mode while trips that incur higher parking fees tend to select transit or SAEV mode, enforcing Catalano et al.'s (2008) finding that carsharing activity can increase with a rise parking fees.

Table 4. Attributes of Private-Vehicle, Transit, and SAEV Trips in Three-Mode Model

		Private Vehicle Trips	Transit Trips	SAEV
Mode Share		60.82%	12.08%	27.10%
VOTT ($/hr)	Average	$17.97	$3.62	$19.62
	Median	$12.50	$2.80	$13.30
	Std Dev	$16.54	$3.15	$19.13
	Max	$92.50	$24.20	$92.50
	Min	$0.00	$0.00	$0.00
Trip Distance (mi)	Average	7.78	19.42	10.74
	Median	5.00	12.00	5.25
	Std Dev	8.05	21.37	12.51
	Max	100.00	150.25	77.00
	Min	1.00	1.00	1.00
Avg Private Vehicle Parking Cost		$0.27	$0.88	$0.56
Avg Transit Access & Wait Time (min.)		65.82	45.17	68.04

Note: Transit trips do not carry parking costs, and PV trips do not involve transit access and wait times. Table values reflect the attributes of the competing (and the chosen) models.

To test how model results vary with parameter changes to the SAEV utility function, sensitivity testing was conducted by looking at higher and lower SAEV fares and valuation of SAEV IVTT (using simple distance-based pricing). In the base three-mode model, SAEV IVTT was valued at 35% of the cost of private vehicle IVTT, based on evaluation of seated IVTT on transit modes. However, travelers are likely to prefer the privacy and comfort of SAEVs over the often shared and not-always guaranteed seated space on buses and trains. To reflect this preference, a lower VOTT value (25% of private vehicle VOTT) was assigned in one sensitivity analysis scenario. Alternatively, while being free of driving obligations is a distinct advantage for SAEVs, the type of productive or leisure activity that can be pursued while traveling in a vehicle is still limited. Cyganski et al. (2015) conducted a stated preference survey on AV use and found that only 13% of respondents reported the ability to work as a primary advantage of AVs over manually-driven vehicles. To ensure that the ability to pursue alternative activities while in a SAEV is not overvalued, the sensitivity analysis here also includes a scenario where SAEV VOTT is valued at 50% of private vehicle VOTT. Mode choice model results (shown in Figure 3a) reveal that the SAEV VOTT seems to have little impact on transit mode share. As the value of SAEV VOTT approaches that of private vehicle VOTT, SAEV loses market share (almost directly) to private vehicles, with relatively few SAEV trips switching to transit mode. These findings suggest that the relative utility of SAEVs is highly dependent on the individual traveler's choice of in-vehicle activity and valuation of that activity as compared to driving. Cyganski et al. (2015) found that higher income travelers are more likely to work in AVs than lower income travelers, further implicating SAEVs' attractiveness for high-VOTT travelers on longer, and thus more work-productive, trips.

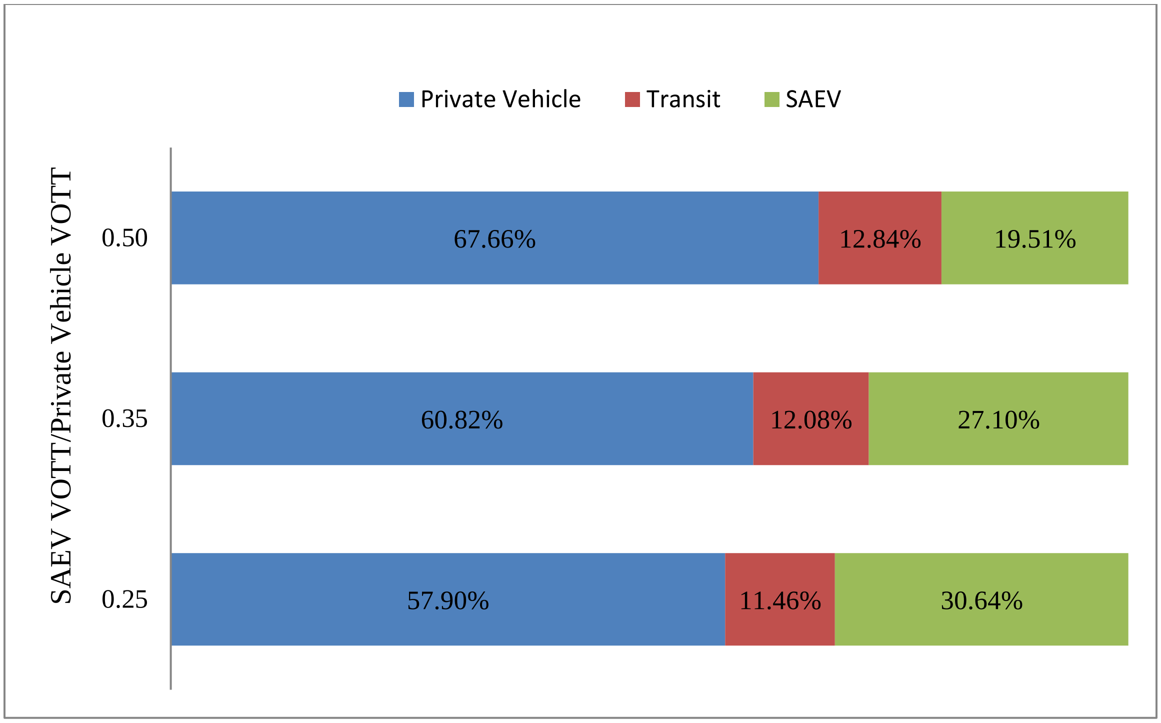

Figure 3a. Mode Share Sensitivity to SAEV VOTT Effects

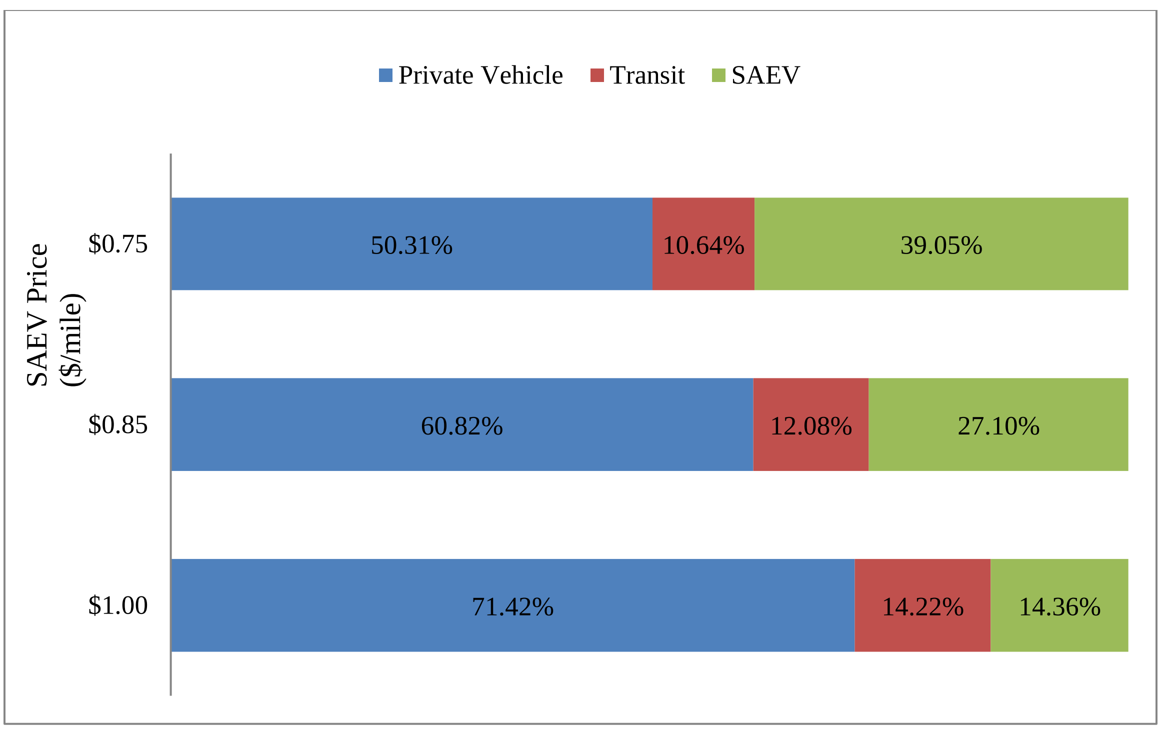

Figure 3b. Mode Share Sensitivity to SAEV Fares

In the base three-mode model, SAEV fare is set at $0.85 per mile. With varying operator missions (whether it be private operators wishing to maximize profit or public agencies focusing on reduction of congestion and mobile emissions), the price of SAEV service can differ drastically. This sensitivity analysis examines the impact of a higher SAEV fare ($1.00 per mile) and a lower SAEV fare ($0.75 per mile) on mode shares. Mode choice model results (shown in Figure 3b) show that a higher SAEV fare causes SAEV service to lose market share to mostly private vehicles (with some trips switching from SAEVs to transit), further confirming SAEV's substitutability for private vehicles for high-income travelers. Elasticities show that private vehicle mode is slightly more sensitive to SAEV VOTT valuation than transit mode: For a 1% increase in SAEV VOTT, private vehicle mode share is predicted to increase 0.58% and transit mode share by 0.56%. On the other hand, variation in SAEV pricing demonstrates that transit mode share is more sensitive than private vehicle mode share to SAEV fare. For a 1% increase in SAEV fare, private vehicle mode share is expected to increase by 0.94% and transit mode share by 1.00%.

As SAEV VOTT and fare parameter changes increase and decrease projected SAEV mode share, the number (and concentration) of SAEV trips in the gridded region also changes. The agent-based model results (Table 5) show the effects of this change in SAEV trip demand on service metrics such as SAEV fleet size, average user wait times, and induced empty VMT (for relocation and charging). When SAEV mode share increases with Low SAEV VOTT and Low Price scenarios, the denser SAEV trip demand lead to decreased user wait times (by 4.8 and 12.2% compared to the base case) and increased vehicle utilization (as measured by the average daily miles per vehicle, which are 7.4 to 19.1% higher than the base case). Increase in SAEV trips also allows vehicles to travel fewer miles for traveler pickup, decreasing total induced empty VMT in the Low SAEV VOTT and Low Price scenarios by 16.1 and 26.5%, respectively, compared to the base case. Because trip characteristics (such as distance and traveler VOTT) are drawn from the same distributions for all region cells, there are only small decreases in empty VMT for relocation and charging purposes as a result of increased SAEV trip concentration. In other words, because there are no zonal variations in sociodemographic characteristics in this model, the geographic spread of SAEV trip demand is relatively consistent regardless of demand intensity.

Table 5. SAEV Fleet Metrics across Sensitivity Analysis Scenarios

	Base	**Low SAEV VOTT**	**High SAEV VOTT**	**Low Price**	**High Price**
SAEV VOTT (as % of Private Vehicle VOTT)	35%	25%	50%	35%	35%
Fare ($/mile)	$0.85	$0.85	$0.85	$0.75	$1.00
Fleet Size	84,945	106,686	54,787	137,323	45,496
Total Trips Served per Day	3.90M	4.03M	3.75M	4.26M	3.62M
Avg Daily Miles per Veh	142.7	153.3	125.0	169.9	105.0
Avg Daily Trips per Veh	45.9	37.7	68.4	31.0	79.6
Avg Trip Distance (mi)	10.6	11.4	8.50	11.9	8.54
Avg Wait Time Per Trip (min)	3.11	2.96	3.36	2.73	3.62
% Total "Empty Vehicle" Miles Traveled	7.70%	7.19%	9.06%	6.76%	9.43%
% of Empty VMT for Relocation	2.79%	2.76%	2.87%	2.69%	2.70%

% of Empty VMT for Charging	1.81%	1.83%	1.77%	1.79%	1.82%
% of Empty VMT for Traveler Pickup	3.10%	2.60%	4.43%	2.28%	4.90%
Max % of Concurrent In-Use Vehicles	38.6%	41.5%	34.7%	48.1%	29.1%
Max % of Concurrent Charging Vehicles	53.5%	54.1%	47.99%	58.0%	40.7%
Operational Cost per Equivalent Occupied Mile Traveled	$0.389	$0.383	$0.400	$0.378	$0.409
Daily Revenue	$9.41M	$12.8M	$5.24M	$16.2M	$4.29M
Revenue-to-Cost Ratio	2.00	2.04	1.92	1.85	2.19

Interestingly, the average trip distance of scenarios with high SAEV trip demand (Low SAEV VOTT and Low Price) are longer than those of scenarios with low SAEV trip demand (High SAEV VOTT and High Price). So while the vehicles in high-demand scenarios are utilized for more miles each day, they actually serve fewer trips per day. However, the households who take these longer trips as SAEV VOTT and fare decrease are different, as reflected by the revenue to cost ratios. Both the Low SAEV VOTT and Low Price scenarios demand a bigger fleet (to serve increased SAEV demand) compared to the base case, but the Low SAEV VOTT scenario registers a bigger profit margin than the base case while the Low Price scenario does the opposite. As discussed previously, travelers who can do productive work while traveling in a SAEV will view their time in a SAEV as less costly, especially as trip distances increase. In the Low SAEV VOTT scenario, more high income travelers' longer trips are captured by SAEV mode. On the other hand, the Low Price scenario captures longer trips from lower income travelers, as the advantage of SAEVs' shorter wait times outweigh the fare advantage of transit in trips that travel between suburban and exurban zones.

Overall, the largest absolute daily revenue is generated by the Low Price scenario, simply due to the significantly increased trip demand. However, when revenue is compared to costs, the High Price scenario yields the most favorable ratio.

Origin, Destination, and Combination Pricing

Sensitivity testing results revealed that different assumptions in SAEV VOTT and fare results in a wide range (14-39%) of SAEV mode shares. These different trip demands require different infrastructure investments and location placements to accommodate increasing and decreasing trip densities. They also heavily impact revenue and profit margins, as shown in Table 5.

Next, this study analyzes how various pricing strategies can affect fleet operations (with the same vehicle fleet size, charging infrastructure, and trip demand). Table 6's results employ the charging strategies described in the Mode Choice Methodology section, all assuming SAEV VOTT to be 35% of private vehicle VOTT and a base distance pricing of $0.85 per mile.

Pricing Scheme	**Distance-Based**	**Origin-Based**	**Destination-Based**	**Combo**
Private Vehicle Mode Share	60.8%	63.9%	67.2%	68.6%
Avg Private Vehicle VOTT ($/hr)	$17.97	$17.57	$17.01	$17.57
Avg Private Vehicle Trip Distance (mi)	7.78	8.31	7.67	8.16
Transit Mode Share	12.1%	11.7%	12.0%	13.1%
Avg Transit VOTT ($/hr)	$3.62	$3.58	$3.31	$3.57
Avg Transit Trip Distance (mi)	19.4	19.1	18.2	18.7

SAEV Mode Share	27.1%	24.4%	20.8%	18.3%
Avg SAEV VOTT ($/hr)	$19.62	$18.78	$21.92	$23.17
Avg SAEV Trip Distance (mi)	10.6	10.1	12.6	12.2
Total Trips Served per Day	3.90M	3.85M	3.72M	3.68M
Avg Daily Miles per Veh	142.7	122.6	117.1	101.2
Avg Daily Trips per Veh	45.9	45.3	43.9	43.3
Avg Wait Time Per Trip (min)	3.11	2.51	3.03	2.40
% Total "Empty Vehicle" Miles Traveled	7.70%	8.11%	7.37%	7.83%
% of Empty VMT for Relocation	2.79%	3.72%	3.11%	4.24%
% of Empty VMT for Charging	1.81%	1.98%	1.80%	2.02%
% of Empty VMT for Traveler Pickup	3.10%	2.41%	2.46%	1.57%
Operational Cost per Equivalent Occupied Mile Traveled	$0.389	$0.398	$0.395	$0.405
Daily Revenue	$9.41M	$8.16M	$8.35M	$7.27M
Revenue to Cost Ratio	2.00	1.97	2.12	2.08

Table 6: SAEV Fleet Metrics across Distinctive Pricing Strategies

Compared to distance-based pricing, the origin-based pricing scheme seems effective in reaching a more balanced vehicle supply and demand. This is reflected by the 22.3% reduction in unoccupied VMT for traveler pickup (compared to distance-based pricing), which then corresponds to a 19.3% reduction in average SAEV wait times. However, this efficiency improvement comes with a 10% reduction in SAEV demand (mode share drops from 27.1% in distance-based pricing to 24.4% in origin-based pricing) and 13.3% decrease in daily revenue. The disproportionate revenue reduction is a result of discounted SAEV trips being more accessible to lower-VOTT households, as witnessed in the 4.3% reduction in average SAEV VOTT between distance- and origin-based pricing.

Destination-based pricing, compared to distance-based pricing, exhibits a negligible (less than 1%) reduction in empty VMT for charging purposes. Due to the coverage-maximizing nature of the charging station site generation methodology used here (discussed in detail in Chen et al. [2016]), the distance between the destination cell and the nearest charging station varies little. However, this pricing scheme did have the effect of discouraging shorter trips from choosing SAEV mode, as the charging surcharge of the SAEV fare becomes a larger portion of the overall fare as trip distances decrease. As discussed previously, high-VOTT travelers favor long SAEV trips. Thus, the decrease in short SAEV trips is accompanied by an 11.7% increase in average SAEV VOTT.

The combination pricing scheme results shows some characteristics of both the origin- and destination-based pricing schemes: Average SAEV wait times are reduced by 22.8% and average SAEV VOTT increases 18.1%. The performance metrics of the combination pricing scheme seems to have two aspects which appeal to time-sensitive/high-VOTT travelers: minimized wait times and pricing which favors longer-distance trips. This pricing scheme also resulted in the highest transit mode share and lowest SAEV mode share.

SUMMARY AND CONCLUSIONS

This study explores the impact of pricing strategies on SAEV market share in a discrete-timed agent-based model of a simulated region with private vehicle, transit, and SAEVs serving as the mode choice alternatives. The model specification delivers roughly an 85%/15% split between private vehicles and transit trips before the introduction of SAEVs. When the SAEV mode is offered at $0.85 per mile (and users are assumed to value SAEV IVTT at 35% the cost of private vehicle IVTT), the model estimates that 27% of all person-trips in the region (of at least 1 mile in distance) will select SAEVs (with 90% of these trips previously choosing private vehicle travel, before introduction of SAEVs).

Sensitivity analysis suggests that SAEV market share can range from 14% to 39% under plausible variations in SAEV VOTT and fare assumptions. Under all scenarios, SAEVs prove to be substitutable for private vehicle travel, assuming that single-occupant shared vehicle trips offer equal utility as single-occupant private vehicle trips for all trip types While private vehicle mode share is most sensitive to persons' VOTT during SAEV travel, transit mode share is most sensitive to SAEV fare assumptions. These results suggest that once EV and AV technologies gain market maturity and become less costly, low-VOTT trip makers will start to choose SAEVs over transit, particularly in areas with poor transit service (as reflected by longer transit-access and wait times), echoing findings from Levin and Boyles' (2015) center-city, peak-period simulation. Model results also suggest that SAEVs will attract longer trips away from private vehicles, particularly among high-VOTT travelers who find SAEV travel much less burdensome than driving. Vehicle features that encourage and enhance work productivity (such as reliable WiFi, ergonomic work surfaces and seating, and reduced road noise) will likely attract longer trips from high-VOTT travelers willing to pay higher fares (Mokhtarian et al. 2013). Like airlines, public SAEV operators may find the best balance of profitability and service completeness by offering a refined, work-enhancing vehicle environment at higher fares to serve high-VOTT travelers (similar to the first- and business-class airplane cabins) and a discounted, sufficiently basic service to serve low-VOTT travelers (similar to economy-class airplane cabins).

Model outputs from various SAEV pricing schemes show that specific fleet metrics can be improved via targeted strategies. For example, fares that seek to balance available SAEV supply with anticipated trip demand (over space and time) can decrease average wait times by 19 to 23%, demonstrating the effectiveness of congestion pricing in a vehicle-balancing framework. However, trade-offs are evident in these pricing schemes: fare structures that favor higher revenue-to-cost ratios (by targeting higher-VOTT travelers) inevitably reduce SAEV mode shares, while those that favor greater market share (by appealing to a wider range of travelers and VOTTs) inevitably produce lower revenue-to-cost ratios. These pricing outputs emphasize the role of the SAEV operators' goals when selecting a fare structure. For private SAEV operators, whose goal typically is to maximize profits, a combination pricing scheme that minimizes user wait times while discouraging shorter trips (which tend to incur a higher level of empty VMT-to-occupied VMT) are most suitable. For a public SAEV operator, whose goal presumably is to maximize equitable access to SAEVs while still reducing wait times, a supply-and-demand (origin-based) pricing scheme may be most suitable.

The model outputs also reinforce the importance of efficient parking prices, since SAEVs will be more competitive against private vehicles in areas which prices parking marginally according to usage rather than subsidies through development policies (e.g. requiring developers to provide specific numbers of parking spaces per retail square footage) or employer-provided benefits.Under-priced and inefficiently-priced parking spaces in most U.S. and non-U.S. cities play a direct role in increasing traffic congestion, housing inaffordability, sprawl, and mobile-source emissions (Litman 2011). Inefficient parking prices also cause undervaluation of one of

SAEVs' key benefits: reduced parking demand (and out-of-pocket parking costs), decreasing their competitive advantage relative to private vehicles.

The pricing strategies and sensitivity analysis explored here offer insights on the many factors that influence SAEV mode shares and fleet performance. However, this agent-base model and application is limited in various ways. For example, more than three modes are possible, including privately-held AVs, which may become very popular, so a vehicle-ownership model (upstream) is needed, along with non-motorized modes and trip distances below 1 mile. Furthermore, a shared-vehicle trip may not offer the same utility as a privately-owned-vehicle trip for all trip types. For example, the transport of children and the elderly frequently require special equipment (carseats and wheel-chair accessible features) that may not be available in fleet vehicles. Nevertheless, while autonomous driving technology is in its infancy (and expensive), SAEVs offer users access to AV technology without significant up-front investment. Additionally, as mentioned in the results discussion, the lack of more individual trip-maker and trip-type attributes over space and time (by time-of-day and day-of-year) oversimplifies the mode (and destination) choice process. In reality, urban geography is highly heterogeneous in terms of trip generation and attraction rates, by time of day and across demographic characteristics. Moreover, trips are segments of complex tours with a variety of constraints on them. More clustered origins and destinations, and routing opportunities may make the systems more efficient, but variations over the days of week and months of year may make fixed fleets less able to serve all comers. Fortunately, pricing can be made flexible, and vehicles can hold more than one traveler, so operators have a variety of price-setting strategies to explore. The future is uncertain, but interesting and full of opportunity for those who make use of these new technologies in socially meaningful ways.

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REFERENCES

AAA (2014) Your Driving Costs: How Much Are You Really Paying to Drive? Available at: http://publicaffairsresources.aaa.biz/wp-content/uploads/2014/05/Your-Driving-Costs-2014.pdf

APTA (2013) 2013 National Transit Data Tables: Urbanized Area Data. Available at: http://www.apta.com/resources/statistics/Pages/NTDDataTables.aspx

Barth, M. and Todd, M. (1999) Simulation Model Performance Analysis of a Multiple Station Shared Vehicle System. *Transportation Research Part C* 7, pp.237-259.

Bierstedt, J., Gooze, A., Gray, C., Peterman, J., Raykin, L. and Walters, J. (2014) *Effects of Next-Generation Vehicles on Travel Demand and Highway Capacity*. January 2014. FP Think. Available at: http://orfe.princeton.edu/~alaink/Papers/FP_NextGenVehicleWhitePaper012414.pdf

Burns, L., William J., and Scarborough, B. (2013) Transforming Personal Mobility. The Earth Institute – Columbia University. New York.

Catalano, M., Lo Casto, B. and Migliore, M. (2008). Car sharing demand estimation and urban transport demand modelling using stated preference techniques, *European Transport*, 40, 33-50.

Chen, T.D., Kockelman, K.M., and Hanna, J.P. (2016) "Operations of a Shared, Autonomous, Electric Vehicle Fleet: Implications of Vehicle & Charging Infrastructure Decisions" forthcoming in *Transportation Research Part A: Policy and Practice.*

Childress, S., Nichols, B., Charlton, B., and Coe, S. (2015) "Using an Activity-Based Model to Explore Possible Impacts of Automated Vehicles," presented at the 94th Annual Meeting of the Transportation Research Board. Washington, DC, January 2015.

Concas, S. and Kolpakov, A. (2009) "Synthesis of Research on Value of Time and Value of Reliability." Center for Transportation Research Report #BD549-46, University of South Florida. Available at: http://www.nctr.usf.edu/pdf/77806.pdf

Correia, G.H. and Antunes, A.P. (2012) "Optimization Approach to Depot Location and Tripl Selection of One-Way Carsharing Systems," *Transportation Research Part E: Logistics and Transportation Review* 48(1), pp.233-247.

Cyganski, R., Fraedrich, E., and Lenz, B. (2015) "Travel-Time Valuation for Automated Driving: A Use-Case-Driven Study," presented at the 94th Annual Meeting of the Transportation Research Board. Washington, DC, January 2015.

Fagnant, D. and Kockelman, K.M. (2014). The Travel and Environmental Implications of Shared Autonomous Vehicles, Using Agent-Based Model Scenarios. *Transportation Research Part C* Vol (40): 1-13.

International Transport Forum (2015) *Urban Mobility System Upgrade: How Shared Self-Driving Cars Could Change City Traffic*, OECD Corporate Partnership Report, May 2015.

Kornhauser, A. (2013) PRT Statewide Application: Conceptual Design of a Transit System Capable of Serving Essentially All Daily Trips. *Urban Public Transportation Systems 2013*: pp. 357-368.

Levin, M.W. and Boyles, S.D. (2015) Effects of Autonomous Vehicle Ownership on Trip, Mode, and Route Choice, presented at the 94th Annual Meeting of the Transportation Research Board. Washington, DC, January 2015.

Litman, T. (2011) *Parking Pricing Implementation Guidelines.* Victoria Transport Policy Institute, March. Available at: http://www.vtpi.org/parkpricing.pdf

McKenzie, B. and M. Rapino (2011) *Commuting in the United States: 2009.* American Community Survey Reports #ACS-15, US Department of Commerce Economics and Statistics Administration, September. Available at: *https://www.census.gov/prod/2011pubs/acs-15.pdf*

Mokhtarian, P.L, Neufeld, A.J., Dong, Z., Circella, G. (2013) Did Free Wi-Fi Made a Difference to Amtrak's Capitol Corridor Service? An Evaluation of the Impact on Riders and Ridership. Institute of Transportation Studies Research Report UCD-ITS-RR-13-03, University of California, Davis. Available at: http://www.its.ucdavis.edu/research/publications/publication-detail/?pub_id=1845

Plug in America (2015) The Promotion of Electric Vehicles in the United States: A Landscape Assessment, May 2015. Available at: http://images.pluginamerica.org/Landscape/The-Promotion-of-Electric-Vehicles-in-the-US-final.pdf

Santos, A., McGuckin., N., Nakamoto, Y., Gray, D., and Liss, S. (2011) Summary of Travel Trends: 2009 National Household Travel Survey. Federal Highway Administration Report #FHWA-PL-11-022. Washington, D.C.

Shoup, D. and Breinholt, M.J. (1997) "Employer-Paid Parking: A Nationwide Survey of Employers' Parking Subsidy Policies," in *The Full Social Cost and Benefits of Transportation*. Eds. D. Greene, D. Jones and M. Delucchi. Heidelberg: Springer-Verlag, pp. 371-385.

Spieser, K., Ballantyne, K., Treleaven, K., Zhang, R., Frazzoli, E., Morton, D., and Pavone, M. (2014). "Toward a Systematic Approach to the Design and Evaluation of Automated Mobility-on-Demand Systems: A Case Study in Singapore." In G. Meyer and S. Beiker (Eds.), *Road Vehicle Automation: Lecture Notes in Mobility* (pp. 229-245). Switzerland: Springer International Publishing.

US Census (2009) Table 702: Money Income of People-Selected Characteristics by Income Level: 2009. Available at: http://www.census.gov/compendia/statab/cats/income_expenditures_poverty_wealth.html

US Department of Transportation (2011) Revised Departmental Guidance on Valuation of Travel Time in Economic Analysis. Memorandum, September 28. Available at: http://www.transportation.gov/sites/dot.dev/files/docs/vot_guidance_092811c.pdf

Wardman, M. (2014) Valuing Convenience in Public Transport. International Transport Forum Discussion Paper 2014-02, April. Available at: http://www.internationaltransportforum.org/jtrc/DiscussionPapers/DP201402.pdf